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Fuzzy Comprehensive Appraisal and SSA-BP Neural Network for the analysis of Sports Smart Bracelet

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Abstract

The second major contribution of this study is the use of the SSA-BP neural network to conduct a comprehensive assessment of sports intelligence bracelets without resorting to cumbersome and perhaps erroneous weight estimations. These results show that the SSA-optimized BP neural network model can predict and assess smart wristband mobility quickly and correctly. Despite the research's limitations, the results are intriguing, suggesting more study is warranted. (1) Using the same analytic hierarchy process, entropy weight technique, and fuzzy comprehensive evaluation approach that we use to evaluate individual products, we wish to analyse the design of many auxiliary decision-makers in order to select the best auxiliary decision-makers for plan optimization. To start an intelligent optimization process, it is necessary to establish important parameters. Reduce modelling error and improve forecast accuracy in item assessment by doing further study into the optimum parameter selection processes.

Introduction

These days, it's hard to find someone who isn't overweight or obese [1]. The rates of overweight and obesity in China have increased steadily since 1980, and are presently 41.2% and 12.9%, respectively [2]. Obesity has been linked to a higher risk of mortality, according to studies [3, 4]. Several sources [5, 6] recommend engaging in regular physical activity to improve one's health. This means that regular participation in sports and physical activity is crucial in the fight against chronic illness [7]. Confidence may be boosted by using AI-powered exercise equipment that creates customized workout routines, according to many research [8, 9]. While smart sports wristbands are a popular example of intelligent wearable technology in sports today [10, 11], they are far from the only option. Therefore, user experience research on current goods before developing new sports smart wrist bands makes it simpler to gather data and analyse health records to monitor physiological data while exercising [12]. Several academics have systematically examined goods using a wide variety of evaluation approaches to better inform designers' judgments throughout the design and implementation phases. In Hinda WI's Computational Intelligence and Neuroscience, Volume 2022, Article ID 5597662, 14 pages (https://doi.org/10.1155/2022/5597662), Zheng et al. [13] used a fuzzy analytic hierarchy process to create a comprehensive model of user satisfaction of public fitness equipment and to uncover users' emotions while using the equipment. Through an importance-performance analysis (IPA) quadrant diagram, we were able to visualize the relative weight of different aspects of the device's performance in relation to the quality of the user

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experience, which in turn helped us to zero in on the areas that needed the most attention in terms of optimization and enhancement based on user feedback. More consideration should be given to the physical and psychological factors of the elderly when designing health application procedures, as suggested by Xia et al. [14], who evaluated health apps for the elderly using a hybrid of analytic hierarchy process (AHP) and a fuzzy comprehend save evaluation method. Using an AHP-fuzzy CGE hybrid, Chang et al. [15] developed a quantitative assessment technique for sweeping machine design. The model compared three distinct approaches to the design of compact electric four-wheel sweepers and settled on one that may serve as a benchmark for future comparisons. Using the entropy TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method, Li et al. [16] established a product optimization evil action model for the Kindle e-reader and provided their expert opinion on how to best optimize and develop the Kindle line of electronic creative products. Hayat et al. [17] advise utilizing TOPSIS to examine customer preferences after weighting them using Shannon entropy to account for customers' needs for acceptability and satisfaction levels. The results verify the efficacy of this method, demonstrating its capacity to provide a versatile and useable framework from which a wide range of clients may choose suitable design solutions. Additionally, the thorough assessments of pertinent themes by professionals have bolstered our job. Technology advancement, market growth, and infrastructure development were only some of the subjective and objective factors Ma et al. [18] used to compare the state of new energy vehicles in China, Japan, Germany, and the United States. Although Germany ranks first in aggregate improvement, it is not the leader in any of the specific measures. The AHP, EWM, and fuzzy comprehensive assessment technique used by Zhang et al. [19] to evaluate Wuhan's water resource value should help the government determine a fair price for water, value local natural resource assets, and create natural resource balance sheets. One can observe that only Zheng et al. [13], Xia et al. [14], and Chang et al. [15] directly integrate the AHP and fuzzy comprehensive assessment by looking at Table 1. When determining what to include in a product, AHP is subjective. Due to the lack of precision and objectivity in the relative worth of design components, we are unable to definitively determine which design scheme is superior. Although the EWM has been used by many researchers, only Li et al. [16] and Hayat et al. [17] employ it. The EWM relies heavily on index data mining and may be readily disentangled from the real scenario of assessment. The AHP and EWM were used by Ma et al., Zhang et al., and Ma et al. [18, 19] to integrate subjective and objective approaches.

Table 1: Recent literature on the comprehensive evaluation methods

Author	AHP	EWM	FCE	Product evaluation
Zheng et al. [13]	√		√	√
Xia et al. [14]	√		√	√
Chang et al. [15]	√		√	√
Li et al. [16]		√		√
Hayat et al. [17]		√		√
Ma et al. [19]	√	√		
Zhang et al. [18]	√	√	√	

By combining AHP and EWM, we come to a more complete assessment using fuzzy comprehensive evaluation (FCE) (AHP). With the purpose of improving the trustworthiness of product assessment and providing designers with a solid basis on which to make choices, we integrate two thorough weighing procedures from the disciplines of CI and NS to examine the sports smart bracelet. (3)) If we were to employ an SSA-optimized BP neural network to do a thorough review of the sport's smart bracelet, we could avoid time-consuming computations of weight in favour of swiftly getting evaluation findings without sacrificing the quality of our judgments. The remaining sections of the paper are structured as follows: Section 5 verifies the method's application in practice, and Section 6 provides a summary and recommendations for further study. Wearable fitness trackers and other high-tech sports equipment are evaluated in Section 5. Section 2 chooses an evaluation indicator for the sport's smart bracelet; Section 3 lays the groundwork with the AHP and EWM; Section 4 builds the comprehensive score prediction model with the SSA-BP neural network. Section 5:

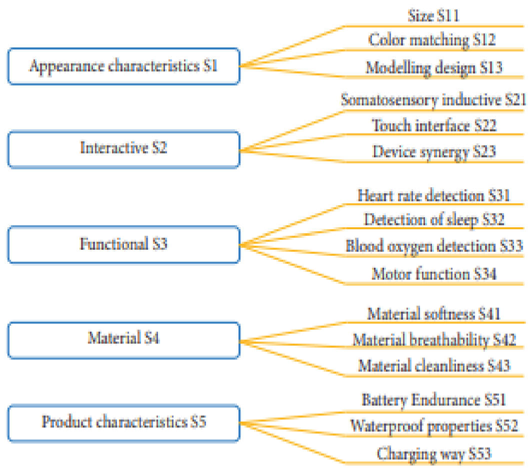

Figure 1: Sports smart bracelet user experience indicator system

Size, interface design, clear interface, heart rate detection, motion function, and material elasticity were identified as preliminary important evaluation indicators based on the results of existing evaluation methods for product design schemes and the characteristics of the smart sports bracelets [23]. In-depth surveys were administered to 10 regular users of sports smart wristbands to provide insight into their experiences with the devices, and the model was refined by adding or removing signals based on the survey results. After finishing the model, we interviewed three experts in industrial design and asked them open-ended questions on the validity of the model's metrics. Below is a summary of the changes that have been made: In order for a "touch interface" to be effective, it is necessary to first consider relevant ideas such a pleasing "shell" and "interface," a manageable "size," straightforward "interface navigation," a practical "interface design," and a transparent "interface." Through in-depth conversations with actual end-users, we were able to clear up any confusion around concepts like "elasticity," "skin affinity," and "multiple selection." Finally, "product performance" is included as an indicator element since it is derived from the user's description of the product's value-add. In the research, 16 different criteria were ranked from best to worst using a scale from 1 to 5. (Physical attributes, interaction, usability, construction, and qualities of the product itself). Figure 1 depicts metrics for evaluating the usefulness of smart wristbands in athletic competition.

Developing a Better Method for Evaluating Smart Athletic Bracelets and a Matrix for Doing So 3.1.

We developed a set of standards for evaluating the reliability of user reviews and the precision of rating results. We created the following relation matrix to depict the links between indicator items and fuzzy membership levels:

$$T = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ t_{21} & t_{22} & \cdots & t_{2n} \\ \vdots & \vdots & & \vdots \\ t_{m1} & t_{m2} & \cdots & t_{mn} \end{bmatrix} \left(0 \le t_{ij} \le 1\right), \tag{1}$$

The item in the itch row and the column is denoted by tin, where I is an indicator and j is a comment. Methods for Evaluating Evaluation Instruments 3.2. The AHP was used to get a rough idea of the weight, and then the EWM was used to get an objective reading; the two were combined to get the final weighing procedure. Then we added up all the information we had gathered. AHP was created in 1970 by an American specialist in operational research named Saaty, and it has since been widely used in the context of decision-making [24–26]. In order to rank the relative importance of the several criteria, the AHP [27] scale technique uses a judgment matrix that is generated via pairwise comparisons. After polling professionals for their thoughts on each evaluative question, we were able to compile the following judgment matrix.

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{mm} \\ d_{21} & d_{22} & \cdots & d_{mm} \\ \vdots & \vdots & & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mm} \end{bmatrix} \left(0 \le d_{ij} \le 1\right). \tag{2}$$

Following the stages of the traditional geometric average technique, we do this analysis: Column-wise normalization of the evaluative matrix d is required to get gig.

$$g_{ij} = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}}. \tag{3}$$

(2) Add the row-normalized values together to derive ai:

$$a_i = \sum_{j=1}^{m} g_{ij}, \quad j = 1, 2, \cdots, m. \tag{4}$$

(3) Determine the relative importance by normalizing the ai obtained.

$$\alpha_i = \frac{a_i}{\sum_{i=1}^{m} a_i}. \tag{5}$$

After the judgment matrix is solved and weights are given to each element, an AHP-required consistency test must be conducted to guarantee that all evaluators are using the same line of reasoning and compatible judgment matrices. There must be a constant indicator in the judgment matrix for there to be a CI.

$$\mathrm{CI} = \frac{\lambda_{\max} - m}{m - 1}, \tag{6}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}. \tag{7}$$

The RI is the random consistency index according to Table 2. Maximum, the biggest distinguishing parameter in the evaluation matrix, is indicated by max. There are m factors in a factorization. If CR is less than 0.1, then the criterion for consistency in the judgment matrix is met. When CR falls below 0.1, the assessment matrix has to be tweaked until consistency is established. "The Entropy Weighting Approach" (Section 3.2.2) The field of management and decision control typically use economic weighting of measures (EWM) [28, 29], whereby the relevance of each evaluation indicator is allocated depending on the quantity of information available. The entropy weight increases as the entropy value decreases, indicating that the indicator is more important in the evaluation system whenever the information of the indicator directly changes. Following are the EWM steps that may be derived from the evaluation matrix in (1):

Table 2: Random consistency indicators

Dimension	RI
1	0
2	0
3	0.52
4	0.89
5	1.12
6	1.26
7	1.36
8	1.41
9	1.46
10	1.49
11	1.52
12	1.54
13	1.56
14	1.58
15	1.59
16	1.5943
17	1.6064
18	1.6133
19	1.6207
20	1.6292

In order to remove the impact of physical quantities, "dimensionless processing" may be performed on data.

(1) Conduct dimensionless processing of the original data to eliminate the influence of physical quantities:

$$t'_{ij} = \frac{t_{ij} - t_{ij\min}}{t_{ij\max} - t_{ij\min}}. \tag{8}$$

(2) Calculate the jth grade, the proportion, or contribution of the ith evaluation indicator:

$$p_{ij} = \frac{t'_{ij}}{\sum_{j=1}^{n} t'_{ij}}. \tag{9}$$

(3) Calculate the entropy value of the jth evaluation indicator:

$$e_i = -\frac{1}{\ln m}\sum_{j=1}^{n} p_{ij}\ln\left(p_{ij}\right), \quad 0 \le e_i \le 1. \tag{10}$$

(4) Calculation of difference coefficient is as follows:

$$g_i = 1 - e_i. \tag{11}$$

(5) Determine the weight of evaluation indicators β_i:

$$\beta_i = \frac{g_i}{\sum_{i=1}^{m} g_i}, \quad i = 1, 2, 3, \cdots, m. \tag{12}$$

Data will be precisely weighed using the All-Inclusive Method (version 3.2.3). Assigning weights to each factor in an AHP analysis often relies on the insight of subject matter experts. Even though AHP incorporates the actual evaluations, expert preferences nevertheless play a part in the outcomes. Important to e EMW is data mining for indications, which may be easily divorced from reality. To account for both the experts' background information and the objective evidence of random consistency shown in Table 2, we use an all-encompassing weighting approach. Dimension RI 1 0 2 0 3 0.52 4 0.89 5 1.12 6 1.26 7 1.36 8 1.41 9 1.46 10 1.49 11 1.52 12 1.54 13 1.56 14 1.58 15 1.59 16 1.5943 17 1.6064 18 1.6133 19 1.6207 20 1.6292 4. Creating and properly weighting evaluation indicators using CI and neuroscience data. If you're curious, here's the corresponding equation:

$$w_i = \frac{\alpha_i \beta_i}{\sum_{i=1}^{m} \alpha_i \beta_i}, \quad i = 1, 2, 3, \cdots, m. \tag{13}$$

Fuzzy Comprehensive Evaluation.

The evaluation results for the sports smart bracelet are obtained by applying a multilevel fuzzy comprehensive evaluation model, which involves first establishing the evaluation matrix of each indicator in order to solve the evaluation of the second-level indicator, and then using the matrix established for the second-level indicator to solve the evaluation results of the first-level indicators. Analysis entails the following steps: generating a comment set, constructing a factor set, developing an evaluation matrix, and computing the degree of membership for each indicator in the factor set. Fuzzy evaluation algorithms provide the evaluation vector R from the evaluation matrix T (tin)Mn and the weight vector generated through exhaustive weighting (r1, r2, run).

$$R = W^T T = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_m \end{bmatrix}^T \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ t_{21} & t_{22} & \cdots & t_{2n} \\ \vdots & \vdots & & \vdots \\ t_{m1} & t_{m2} & \cdots & t_{mn} \end{bmatrix} = \left(r_1, r_2, \cdots, r_n\right), \tag{14}$$

where $W = (w_1, w_2, \cdots, w_m)^T$ is the weight of all levels of indicators.

SSA-BP Neural Network

(See Section 4.1 of the Sparrow Search Algorithm for more explanation.) From what we can tell, Xue and Shen [30] were the first to present the sparrow search technique. Swarm optimization is a novel approach to optimization that takes cues from the coordinated efforts of sparrow groups to avoid being eaten. Building an idealized model of a sparrow's behaviour and then controlling its output are the initial steps in using this method. Where Xi [xi1, xi2, xi d] are the positions of the individual birds in a dimensional space D, the fitness function of a flock of n sparrows is given by Fix [xi2 + xi3 + xi4 + xi5 + xi6 + xi7 + xi8 + xi9]. What happens is as follows: (1, 2, 3, xi d) There are sparrows who sleep and others that forage for food. About 10% to 20% of sparrows are constantly scanning the area, and they alert the remainder of the flock by flying through designated "security zones." There are a variety of places to go for up-to-date information on where certain industries are located.

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t+1} \times \exp\left(\dfrac{-i}{\alpha \times iter_{\max}}\right), & \text{if } R^2 < ST, \\ X_{i,j}^{t} + Q \times L, & \text{if } R^2 \geq ST, \end{cases} \tag{15}$$

where it is the current iteration and j is an integer from 1 to d where d is the dimension size. R2 [0, 1] is the caution value, while ST [0.5, 1.0] is the safe zone. Tx imp is the coordinate of the itch sparrow in the dimension at time t, where intermix is the maximum number of iterations. Every element of the matrix L is the same, and the random number Q is distributed normally. A producer goes into a more extensive search mode at R2 ST if there are no known nearby predators. Given that at least one of the sparrows has observed anything potentially harmful, if R2 is less than ST, the birds will quickly escape. The remaining sparrows, those who aren't producers, are volunteers that clean up after the producers.

$$X_{i,j}^{t+1} = \begin{cases} Q \times \exp\left(\dfrac{X_{\text{worst}}^{t} - X_{i,j}^{t}}{i^2}\right), & \text{if } i > n/2, \\ X_{P}^{t+1} + \left|X_{i,j}^{t} - X_{P}^{t+1}\right| \times A^{+} \times L, & \text{otherwise}, \end{cases} \tag{16}$$

where Tx worst is the worst possible location on Earth right now and Xt+1 P is the best possible location for the producer in iteration t+1. In this case, if A is a 1 by d matrix with entries that are both 1, then A+ AT(AAT) = 1, where n is the total number of sparrows. A sparrow's best chance of surviving in a dangerous situation is provided by

$$X_{i,j}^{t+1} = \begin{cases} X_{\text{best}}^{t} + \beta \times \left|X_{i,j}^{t} - X_{\text{best}}^{t}\right|, & \text{if } f_i > f_g, \\ X_{i,j}^{t} + K \times \left(\dfrac{\left|X_{i,j}^{t} - X_{\text{worst}}^{t}\right|}{(f_i - f_w) + \varepsilon}\right), & \text{if } f_i = f_g, \end{cases} \tag{17}$$

Where K [1, 1] is the sparrow's flight direction and a step size control parameter, and Tx best is the current global ideal position, we employ a normal distribution of random numbers with mean 0 and variance 1. The fitness of the current sparrow, fi, is the smallest constant that precludes a zero-division mistake; the fitness of the world's fittest person, fog, and its least fit person, few, are, respectively. If fi > fog, then the sparrow is far from the group average position. The centre sparrows are the ones that see a fi fog scenario first and act upon it. Pineda [31] first described the BP neural network, and that work is included in Section 4.2. (Using a Neural Network to Predict Behaviour). Predicted values are generated by a BP neural network by connecting input layers, hidden layers, and output layers with weights and thresholds. The gradient descent method iteratively changes weights and thresholds in order to minimize the prediction error by comparing the predicted and observed response values. Diagrammatical representation of the algorithm structure is shown in Figure 2.

(1) Suppose that the input layers are $x_i = \{x_1, x_2, \cdots x_i, \cdots x_d\}$, hidden layers are $b_h = \{b_1, b_2, \cdots b_h, \cdots b_q\}$, and output layers are $y_j = \{y_1, y_2, \cdots y_j, \cdots y_l\}$.

2All weights and thresholds are assigned values between 0 and 1 and are indicated by the symbols with and h between the input and hidden layers and he and j between the hidden and output layers. (0, 1).

(3) Calculate the values for hidden layers and output layers by $r_h = f\left(\sum_{i=1}^{d} w_{ih} x_i - \theta_h\right)$ and $y_j = f\left(\sum_{j=1}^{l} v_{hj} b_h - \delta_h\right)$, respectively.

(4) Calculate the overall squared error by $E_k = 1/2 \sum_{j=1}^{l} (\hat{y}_j^k - y_j^k)^2$, where $\hat{y}_j^k$ and y_j^k are the predicted value and true value, respectively.

(5) Calculate the gradient descents for the output layers and hidden layers, which are given by $g_j = \hat{y}_j^k (1 - \hat{y}_j^k)(y_j^k - \hat{y}_j^k)$ and $e_h = b_h (1 - b_h) \sum_{j=1}^{l} \omega_{hj} g_j$, respectively.

(6) Update the corresponding weights and thresholds. In particular, the updated weights for output layers are given by $v_{hj}^{(t+1)} = v_{hj}^{(t)} + \eta g_j b_h$, the updated thresholds for output layers are given by $\delta_j^{(t+1)} = \delta_j^{(t)} - \eta g_j$, the updated weights for hidden layers are given by $w_{ih}^{(t+1)} = w_{ih}^{(t)} + \eta e_h x_i$, and the updated thresholds for hidden layers are given by $\delta_h^{(t+1)} = \delta_h^{(t)} - \eta e_h$, where t is the number of iterations.

If the cumulative number of training-related mistakes is fewer than or equal to some goal, then the training was successful. If the error is still too large after additional training, we begin the procedure again. The SSA-BP neural network approach was created specifically to deal with this problem. To reiterate the point, the BP neural network's gradient descent would never converge to the global minimum. It would be easier to get around these restrictions if the appropriate connection weight and threshold could be determined. To determine the optimal starting values for the connection weight and threshold in a neural network's training, many researchers have turned to intelligent optimization strategies like the Genetic Algorithm (GA), Particle Swarm Opti mutation (PSO), Firefly Algorithm (FA), Grey Wolf Opti miser (GWO), and SSA [32–36]. We trained a BP neural network using the ideal connection weight and threshold values provided by SSA to get the best model.

Figure 3 is a diagrammatic representation of the SSA-BP procedure.

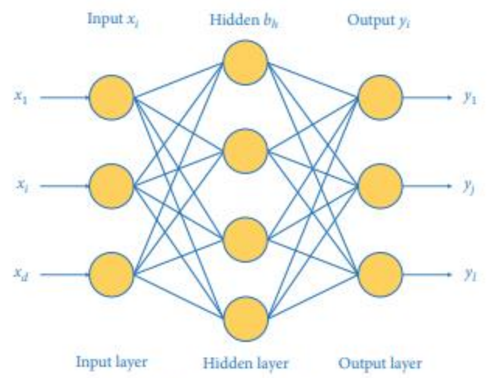

FIGURE 2: BP neural network structure.

Initial BP neural network architecture requires establishing the link weight and threshold. In order to determine the optimal population size, maximum evolutionary algebra, percentage of producers, percentage of risk-aware sparrows, production ratio, and minimal tolerable risk using the SSA approach, we do the following calculations. The final stage involves sorting the sparrows by their fitness levels and conducting the arithmetic to find the best and worst performers. Mathematical adjustments to the producer's position are required before moving on to step 4. (15). Finally, an equation is utilized to pin down the scavenger's specific location (16). Sixth, relocate the vigilant sparrows using the supplied equation (17). Seventh, a new global best solution is found by comparing the sparrow's current location to the old one. Step 8 verifies that the loop terminates as expected. If so, the iteration is complete, the best answer is recorded, and the procedure continues to Step 9; otherwise, it loops back to Step 3. Through a sufficient number of iterations of the SSA method, the BP neural network's connection weights and thresholds are trained to reflect the global optimal solution (step 9).

User Experiences with Sports Smart Bracelets

Huge amounts of information are being gathered right now. The satisfaction of the sports smart bracelet was measured through a 21-question survey.

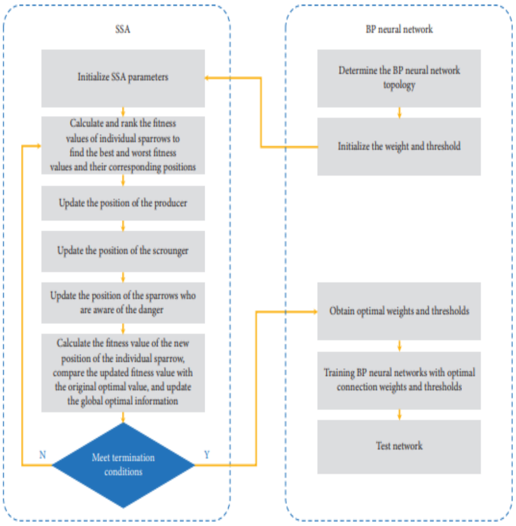

Figure 3: Flow chart of SSA-BP neural network algorithm.

Included in sports smart wristbands was the aforementioned indicator technology, which was used to test customers' familiarity with indicator data. In order to quantitatively assess the results of the survey, a seven-point Likert scale was utilized. Fifty people were the subjects of in-depth interviews and surveys (May 15th, 2021 - June 30th, 2021). Setting up a Decision Matrix Using Heuristics Using a membership function transformation, we generate a fuzzy membership evaluation matrix for each subcomponent of the indicator (the factor set of the comprehensive evaluation model) according to the guidelines laid forth in (see Table 3). Analysis Considerations and Possible Predictive Factors Eleven specialists were consulted, and one of them looked into the signal to determine whether it was significant enough to merit further study. Judgment matrices and weight vectors derived from the experts' ratings are shown in Table 4. (5). Table 2 contains two equations that may be used to validate the reliability of the main and secondary indicators (6, 7). (7). (7). Table 5 presents a compilation of the data. There are no CR values over 0.1 in Table 5, therefore being consistent shouldn't be a problem. Table 3 and Section 5.3.2 provide the data and background upon which the entropy weights approach, which is utilized to build the foundations of many layered indicators, is built.

$$T_1 = \begin{bmatrix} 0 & 0.02 & 0.04 & 0.12 & 0.34 & 0.26 & 0.22 \\ 0 & 0.02 & 0.04 & 0.16 & 0.3 & 0.24 & 0.24 \\ 0.02 & 0.02 & 0.08 & 0.12 & 0.34 & 0.22 & 0.2 \end{bmatrix} \left(0 \le t_{ij} \le 1\right), \tag{18}$$

$$T_2 = \begin{bmatrix} 0 & 0 & 0.06 & 0.2 & 0.18 & 0.38 & 0.18 \\ 0 & 0.04 & 0.06 & 0.18 & 0.22 & 0.3 & 0.2 \\ 0 & 0 & 0.06 & 0.18 & 0.2 & 0.36 & 0.2 \end{bmatrix} \left(0 \le t_{ij} \le 1\right), \tag{19}$$

$$T_3 = \begin{bmatrix} 0 & 0 & 0 & 0.2 & 0.24 & 0.34 & 0.22 \\ 0 & 0 & 0.04 & 0.16 & 0.26 & 0.28 & 0.26 \\ 0 & 0 & 0.04 & 0.22 & 0.24 & 0.32 & 0.18 \\ 0 & 0 & 0.02 & 0.14 & 0.32 & 0.24 & 0.28 \end{bmatrix} \left(0 \le t_{ij} \le 1\right), \tag{20}$$

Table 3: Fuzzy membership evaluation matrix of user experience of sports smart bracelets.

First-level indicators	Second-level indicators	Comment set						
		*P*1	*P*2	*P*3	*P*4	*P*5	*P*6	*P*7
Appearance characteristic S1	Size S11	0	0.02	0.04	0.12	0.34	0.26	0.22
	Color matching S12	0	0.02	0.04	0.16	0.3	0.24	0.24
	Modeling design S13	0.02	0.02	0.08	0.12	0.34	0.22	0.2
Interactive S2	Somatosensory inductive S21	0	0	0	0.2	0.18	0.38	0.18
	Touch interface S22	0	0.4	0.6	0.18	0.22	0.3	0.2
	Device synergy S23	0	0	0.6	0.18	0.2	0.36	0.2
Functional S3	Heart rate detection S31	0	0	0	0.2	0.24	0.34	0.22
	Detection of sleep S32	0	0	0.04	0.16	0.26	0.28	0.26
	Blood oxygen detection S33	0	0	0.04	0.22	0.24	0.32	0.18
	Motor function S34	0	0	0.02	0.14	0.32	0.24	0.28
Material S4	Material softness S41	0	0	0	0.12	0.34	0.3	0.24
	Material breathability S42	0	0.02	0.04	0.16	0.36	0.24	0.18
	Material cleanliness S43	0.02	0	0.12	0.12	0.28	0.28	0.18
Product characteristics S5	Battery endurance S51	0	0.02	0.04	0.12	0.26	0.26	0.3
	Waterproof properties S52	0	0	0.04	0.12	0.26	0.3	0.28
	Charging way S53	0.02	0	0.02	0.12	0.28	0.32	0.24

*Note. P*1 is "very dissatisfied," *P*2 is "dissatisfied," *P*3 is "relatively dissatisfied," *P*4 is "uncertain," *P*5 is "relatively satisfied," *P*6 is "satisfied," and *P*7 is "very satisfied."

Table 4: Weight of user experience evaluation indicators of sports smart bracelets based on AH

Target	First-level indicators	Weights	Second-level indicators	Weights
Sports smart bracelet user experience	S1	0.138	S11	0.444
			S12	0.258
			S13	0.298
	S2	0.244	S21	0.256
			S22	0.364
			S23	0.379
	S3	0.455	S31	0.244
			S32	0.173
			S33	0.139
			S34	0.445
	S4	0.075	S41	0.429
			S42	0.339
			S43	0.232
	S5	0.088	S51	0.486
			S52	0.237
			S53	0.277

Table 5: Consistency test

Level	λ_{max}	CI	CR
All	5.07080	0.01770	0.00002
S1	3.00143	0.00071	0.00120
S2	3.01110	0.00550	0.00960
S3	4.00500	0.00170	0.00180
S4	3.00070	0.00036	0.00061
S5	3.00070	0.00033	0.00057

$$T_4 = \begin{bmatrix} 0 & 0 & 0 & 0.12 & 0.34 & 0.3 & 0.24 \\ 0 & 0.02 & 0.04 & 0.16 & 0.36 & 0.24 & 0.18 \\ 0.02 & 0 & 0.12 & 0.12 & 0.28 & 0.28 & 0.18 \end{bmatrix} \left(0 \le t_{ij} \le 1\right), \tag{21}$$

$$T_5 = \begin{bmatrix} 0 & 0.02 & 0.04 & 0.12 & 0.26 & 0.26 & 0.3 \\ 0 & 0 & 0.04 & 0.12 & 0.26 & 0.3 & 0.28 \\ 0.02 & 0 & 0.02 & 0.12 & 0.28 & 0.32 & 0.24 \end{bmatrix} \left(0 \le t_{ij} \le 1\right). \tag{22}$$

Examine Table 6 to see how the EWM's objective weight vector was computed for each criterion using the aforementioned equations (18)– (22). As can be seen in Tables 7 and 8, the results become more grounded in reality when the AHP and EWM are combined using the entire weighting approach. The 16 criteria for assessment are laid forth in Table 8 and Figure 4. The ability of a product to analyse the user's pulse and motion pattern is highly valued by experts and ratters. The bracelet's major focus is on human health as measured by exercise and heart rate measurement, and a third significant conclusion is that device synergy is connected to interactivity; thus, the speed with which data is sent to the user is an important consideration for sports smart wristbands. The user's ability to control the sports smart bracelet with gestures and touches is more significant than the bracelet's size, colour, and style. worldwide pessimism (5.4). You may figure out a layer's fuzzy complete evaluation by using Tables 3 and 8, together with the accompanying Equation (14).

$$R_1 = W_1^T \times T_1 = (0.0065, 0.02, 0.053, 0.1294, 0.3306, 0.2423, 0.2182),$$

$$R_2 = W_2^T \times T_2 = (0, 0.0115, 0.0601, 0.1860, 0.2001, 0.3490, 0.1943),$$

$$R_3 = W_3^T \times T_3 = (0, 0, 0.0201, 0.1693, 0.2792, 0.2832, 0.2483),$$

$$R_4 = W_4^T \times T_4 = (0.0032, 0.0059, 0.0310, 0.1318, 0.3363, 0.2790, 0.2126),$$

$$R_5 = W_5^T \times T_5 = (0.0058, 0.0091, 0.0342, 0.1200, 0.2658, 0.2876, 0.2775),$$

$$T = \begin{bmatrix} 0.0065 & 0.02 & 0.053 & 0.1294 & 0.3306 & 0.2423 & 0.2182 \\ 0 & 0.0115 & 0.0601 & 0.186 & 0.2001 & 0.349 & 0.1943 \\ 0 & 0 & 0.0201 & 0.1693 & 0.2792 & 0.2832 & 0.2483 \\ 0.0032 & 0.0059 & 0.031 & 0.1318 & 0.3363 & 0.279 & 0.2126 \\ 0.0058 & 0.0091 & 0.0342 & 0.12 & 0.2658 & 0.2876 & 0.2775 \end{bmatrix} \left(0 \le t_{ij} \le 1\right),$$

$$L = W^T \times T = (0.0013, 0.0054, 0.0328, 0.1618, 0.2725, 0.2907, 0.2347).$$

These results show that just 3.95 percent of purchasers are dissatisfied, while the remaining 97.25 percent are delighted with their purchases. Customers gave good ratings to all other parameters (design, interaction, functionality, content, and quality) except usability (53.15%-49.16%). Many customers have complained about the subpar design and craftsmanship. These two factors are of the utmost importance, and they should be prioritized throughout the design process. Analysing the SSA-BP and BP Models using Neural Networks The sports intelligent wristband uses a fuzzy comprehensive assessment to define the user's experience due to the complexity of the weight calculation. Assessment times may be cut down with SSA by training a BP neural network on data from several ratters to provide an accurate prediction of the smart bracelet's overall rating. To do this, we applied the fuzzy comprehensive assessment weights to each of the fifty samples and found that the evaluation score Y was the dependent variable that required work. Where Do Performance Metrics Come From? - Shifting the Reference Point These are the components of the BP neural network: For example, if the number of neurons in the input layer is 16, and the training rate is 0.01, then the maximum number of potential iterations is 1000. To roughly estimate how many neurons are in the deep subsurface layer, one may apply the following empirical formula: (h = 5, h = 14,) The following are examples of SSA initialization parameters: This scenario assumes a beginning population of 30, a safety factor of 0.6, a birth-rate of 0.5, and 20% risk-seeking farmers and 80% risk-averse sparrows. The following factors were considered in our final rating of the model: Common measures of variability include the standard deviation, root-mean-squared error, and mean-squared error (RMSE),

Table 6: Weights of evaluation indicators of user experience of sports smart bracelets based on EWM.

Target	First-level indicators	Weights	Second-level indicators	Weights
			S11	0.332
	S1	0.177	S12	0.305
			S13	0.363
			S21	0.376
	S2	0.169	S22	0.259
			S23	0.365
			S31	0.284
			S32	0.228
Sports smart bracelet user experience	S3	0.277	S33	0.229
			S34	0.259
			S41	0.448
	S4	0.188	S42	0.308
			S43	0.244
			S51	0.304
	S5	0.188	S52	0.356
			S53	0.339

Table 7: Weight of evaluation indicator of user experience of sports smart bracelets based on AHP and EWM

Target	First-level indicators	Weights	Second-level indicators	Weights
			S11	0.441
	S1	0.11	S12	0.235
			S13	0.324
			S21	0.293
	S2	0.185	S22	0.287
			S23	0.421
			S31	0.271
			S32	0.154
Sports smart bracelet user experience	S3	0.567	S33	0.124
			S34	0.451
			S41	0.544
	S4	0.063	S42	0.296
			S43	0.16
			S51	0.453
	S5	0.074	S52	0.259
			S53	0.288

Table 8: Weight of each evaluation indicator relative to the overall goal based on multiple methods

Indicators	AHP	EWM	AHP+EWM
S11	0.061	0.06	0.057
S12	0.036	0.055	0.031
S13	0.041	0.066	0.042
S21	0.062	0.065	0.063
S22	0.089	0.045	0.063
S23	0.092	0.063	0.091
S31	0.111	0.081	0.141
S32	0.079	0.055	0.068
S33	0.063	0.05	0.049
S34	0.202	0.073	0.23
S41	0.032	0.086	0.043
S42	0.025	0.059	0.023
S43	0.017	0.047	0.012
S51	0.043	0.059	0.04
S52	0.021	0.069	0.023
S53	0.024	0.065	0.024

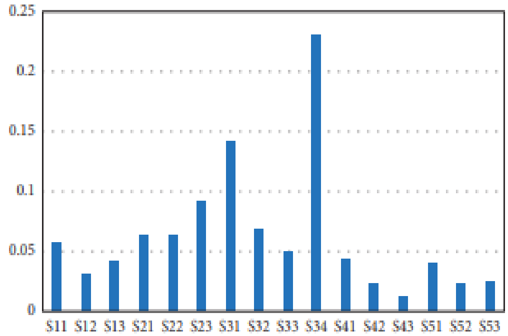

Figure 4: Weight of each evaluation indicator of AHP + EWM relative to the overall goal

Table 9: Evaluation of user experience of sports smart bracelets (part)

Number	S11	S12	S13	...	S51	S52	S53	Y
...	...	...	...	...	...	...	...	...
12	5	5	5	...	5	5	5	5
13	3	3	3	...	5	5	5	4.306
14	5	3	3	...	5	3	5	4.74
15	5	5	5	...	5	5	7	5.067
16	7	2	2	...	7	7	7	5.699
17	6	6	6	...	7	7	6	6.215
18	6	6	6	...	6	6	6	6
...	...	...	...	...	...	...	...	...

$$\begin{aligned} \text{MSE} &= \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2, \\ \text{RMSE} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}, \\ \text{MAE} &= \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right|, \\ \text{MAPE} &= \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right|, \end{aligned} \tag{24}$$

I is the itch observation, n is the total number of observations, and xi and Yi are the predicted and observed values, respectively. An important indicator, the MSE measures how far off the model was from the actual value. The Mean Squared Error (MSE) is a quantitative measure of the model's explanatory power. The RMSE is a more precise deviation measure than the MSE since it is derived by square rooting the MSE. The average absolute error provides a more nuanced assessment of the forecast's degree of uncertainty (MAE). The MAPE is a measure of relative error that is derived by dividing the Mean Absolute Error by the True Value and then multiplying the result by 100.

Determination of the Number of Hidden Layer Neurons.

Figure 5 shows that with 7 neurons in the hidden layer, the trained model has the smallest mean squared error (MSE). We'll evaluate the outcomes and draw conclusions in Section 5.5.3. Figure 6 demonstrates how important it is to include the parameter optimization technique into the BP model by comparing the estimates from the SSA-BP model with the traditional BP model. In addition, we compare and contrast how well different optimization techniques work. Figure 7 shows that compared to the GA-BP and PSO-BP models, the SSA-BP model provides better accuracy. To further verify the accuracy of the predictions, Table 10 compares SSA-BP and BP in terms of their mean absolute error, mean standard error, root mean square error, and mean absolute prediction error (MAE, MSE, RMSE, and MAPE). Table 10 demonstrates that the MAE generated by the SSA-BP model is 98.02% less than that generated by the BP model, 95.97% smaller than that generated by the GA-BP model, and 95.27% smaller than that generated by the PSO-BP model. Using the BP model, the GA-BP model, or the PSO-BP model reduces MSE by 99.97%, 99.84%, or 99.81%, respectively. Using the SSA-BP model, one may get MSE values of 99.9%, 99.84%, and 99.81%, respectively. Results are stable over a wide variety of parameters, including root mean square error (RMSE) and maximum absolute percentage error (MAPE). Results show that when it comes to improving the BP model's prediction accuracy, SSA stands head and shoulders above other optimization approaches like GA and PSO. Benefits of the suggested method were verified by user studies of sports smart wristbands (see Section 5.6). Selecting sixteen tertiary indicators and then subdividing them into five primary indicators was done for this research. We can see that both professionals and consumers put a premium on health-related movement patterns and heart-rate detection by combining the data with the aid of the complete weighted technique, and then calculating the whole weights. Harmony, obtained by body induction, apparatus coordination, and too, is the second major outcome. There is some disagreement on the product's design and quality, but generally, 79.79% of buyers are pleased with their purchase. Smart wristbands for sports are becoming more popular because of their usefulness in bridging the gap between humans and machines. Designers should think about these, especially in terms of aesthetics. The SSA-BP neural network is employed in this study since calculating weights would take too much time.

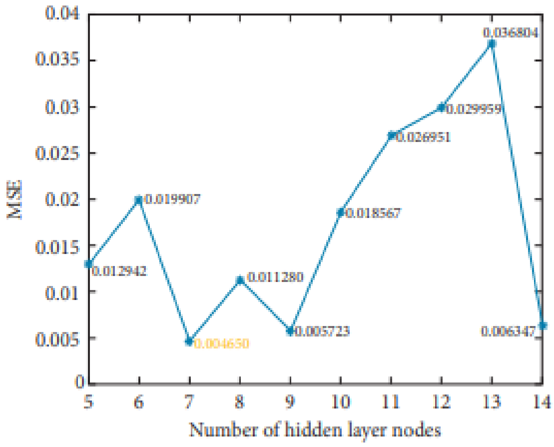

Figure 5: MSE for different hidden layers.

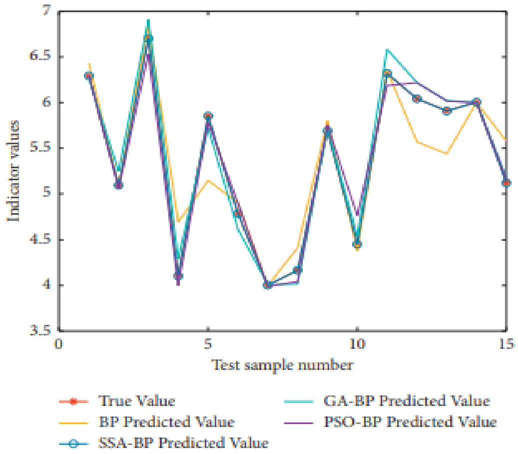

Figure 6: Prediction results of each model.

study of smart wristbands in sports from every angle. Compared to GA-BP, PSO-BP, and the baseline BP models, SSA-BP is found to perform better on the MSE, RMSE, MAE, and MAPE assessment criteria.

Conclusions and Future Work:

Exercise has the potential to help fight the various chronic diseases that have been linked to obesity. One possible use for a high-end sports smart bracelet is to help those who often push their bodies to the limit. There is an urgent need to figure out how to interpret data from a smart sports wristband. In this research, we evaluate the usefulness of smart wristbands for athletes by means of a fuzzy comprehensive evaluation. Although EWM has been shown to be useful in fuzzy comprehensive assessment [38, 39], AHP is used to determine the relative value of each evaluation signal.

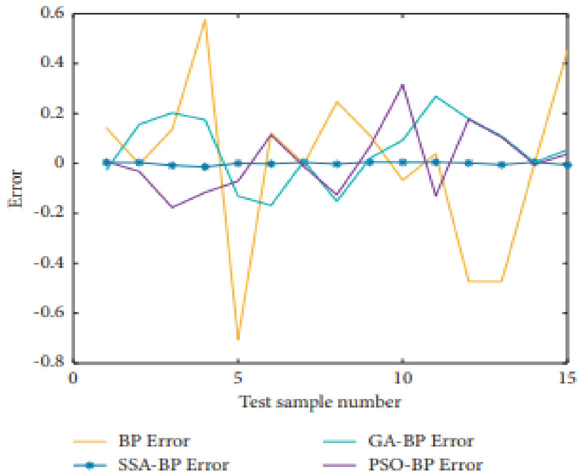

Figure 7: Comparison chart of relative error of each model

Table 10: Performance comparison of each model under different evaluation indicators

Model	MAE	MSE	RMSE	MAPE (%)
BP	0.23657	0.10768	0.32814	4.508
SSA-BP	0.0046943	$3.1148e-05$	0.0055811	0.091783
GA-BP	0.11659	0.019531	0.13975	2.2018
PSO-BP	0.09928	0.016239	0.12743	1.9276

A choice including certain subjective factors is easily attainable within the scope of this inquiry. Because the EWM gives each assessment signal the same weight in the final tally, it might be easy to lose perspective if you use it to determine how your findings are tallied. Using the comprehensive weighting approach, this research combines the two methods to derive the comprehensive weight of the indicator for use in performing the comprehensive evaluation of the product, which will help the decision-maker conduct a more scientific and accurate evaluation of the product and provide a foundation for future decisions regarding the creation of similar products. Sports smart wristbands were evaluated based on a number of criteria, including movement mode, heart rate monitoring, device cooperation, motion sensing, and touch interfaces. After the smoke cleared, users were not excited about the device, therefore the evaluation suggested that designers work on improving the product's design and structure for future versions. The second major contribution of this study is the use of the SSA-BP neural network to conduct a comprehensive assessment of sports intelligence bracelets without resorting to cumbersome and perhaps erroneous weight estimations. These results show that the SSA-optimized BP neural network model can predict and assess smart wristband mobility quickly and correctly. Despite the research's limitations, the results are intriguing, suggesting more study is warranted. (1) Using the same analytic hierarchy process, entropy weight technique, and fuzzy comprehensive evaluation approach that we use to evaluate individual products, we wish to analyse the design of many auxiliary decision-makers in order to select the best auxiliary decision-makers for plan optimization. To start an intelligent optimization process, it is necessary to establish important parameters. Reduce modelling error and improve forecast accuracy in item assessment by doing further study into the optimum parameter selection processes. Therefore, future research may benefit from a variety of approaches, such as ELECTRE III or DEMATEL (Decision-making Trial and Evaluation Laboratory). [40, 41] At the request of the reader, the author will make available the data sets that were analysed and utilized to create the findings shown here Disturbances to the status quo The authors report no conflicts of interest.

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